ARTICLE IN PRESS

Applied Energy xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

When will wind energy achieve grid parity in China? – Connecting technological learning and climate finance ☆

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HIGHLIGHTS

- The learning rate of China's wind energy sector over 2004–2011 is estimated.
- The options to achieve grid-parity for wind electricity are investigated.
- The evolution of learning investment is examined.
- The linkage between learning investment and climate finance is discussed.

ARTICLE INFO

Article history:
Received 4 November 2014
Received in revised form 22 April 2015
Accepted 23 April 2015
Available online xxxx

Keywords:
Learning curve
Climate finance
Technology subsidy
Technological change
Wind energy

ABSTRACT

China has adopted an ambitious plan for wind energy deployment. This paper uses the theory of the learning curve to investigate financing options to support grid parity for wind electricity. First, relying on a panel dataset consisting of information from 1207 wind projects in China's thirty provinces over the period of 2004–2011, this study empirically estimates the learning rate of onshore wind technology to be around 4.4%. Given this low learning rate, achieving grid parity requires a policy of pricing carbon at 13 €/ton CO2e in order to increase the cost of coal-generated electricity. Alternatively, a learning rate of 8.9% would be necessary in the absence of a carbon price. Second, this study assesses the evolution of additional capital subsidies in a dynamic framework of technological learning. The implicit average CO2 abatement cost derived from this learning investment is estimated to be around 16 €/ton CO2e over the breakeven time period. The findings suggest that climate finance could be structured in a way to provide up-front financing to support this paradigm shift in energy transition.

1. Introduction

Reducing greenhouse gas emissions is a two-way street that bridges finance and technology. The key issue of global climate finance is to unlock and scale up additional and predictable capital. Meanwhile, promoting renewable energy is a distinct part of the global climate regime. The long-term policy objective is to make electricity generation from renewable energy sources achieve grid parity without subsidies. Both challenges have prompted policy makers to question whether consistency between these climate and technology mechanisms can be ensured to achieve long-term environmental and energy targets.

To answer this question, the theory of the learning curve provides a useful approach. The unit cost of a product falls along with knowledge accumulation based on learning-by-doing and research and development (R&D) [1]. Dutton and Thomas [2] and Anzanello and Fogliatto [3] provided a comprehensive review on learning models and their application in various industries. Such learning effects were found to be significant for renewable energy technologies (e.g. [4–9]. Understanding the role of technology learning has important policy implications, given the long-term nature of climate and energy challenges. Generally, an early and upfront

☆ This article is based on a short proceedings paper in Energy Procedia Volume 161 (2014). It has been substantially modified and extended, and has been subject to the normal peer review and revision process of the journal. This paper is included in the Special Issue of ICAE2014 edited by Prof. J Yan, Prof. DJ Lee, Prof. SK Chou, and Prof. U Desideri.

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http://dx.doi.org/10.1016/j.apenergy.2015.04.094
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Please cite this article in press as: Yao X et al. When will wind energy achieve grid parity in China? – Connecting technological learning and climate finance. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.04.094

investment support can be justified by economic benefits of faster cost reduction [10]. The success of policy instruments needs to consider this dynamic efficiency.

In this study, we first assess the learning rate of China's wind energy by considering two drivers of learning effects – cumulative installed capacity and technology efficiency improvement. Then, we extend the learning curve model to investigate the evolution of additional capital subsidies needed to trigger grid parity, depending on three technology dimensions – learning rate, cost target, and deployment speed. Finally, we estimate the implicit abatement cost over the breakeven time.

Our contribution is two-fold. First, this study estimates the learning rate of onshore wind energy in China over the time period of its impressive leapfrog in the global wind power market. To this end, we construct a province-wide panel dataset from 2004 to 2011, based on capital costs of 1207 wind power projects. The learning rate is found to be around 4.4%, falling in the low end of the historical estimates of wind power learning rates. The review of the literature leads to few uniform conclusions – the wind power learning rates can range from 4% to 32% [11–13]. The existing studies rely on the data from industrialized countries. Even though China had virtually no wind power capacity in 2001, the country has led the global wind market with the highest installed capacity since 2010 [14]. To our knowledge, the literature to date provides only one estimate of China's wind power learning rate, using the bidding electricity prices of national wind project concession programs from 2003 to 2007 [15]. However, our dataset consists of capital costs of wind projects and covers a more comprehensive time period, thus providing a complementary analysis.

Second, this study extends the analysis of learning investment derived in [16] and investigates a carbon pricing policy in a dynamic framework of technological learning. Previous studies evaluated the abatement cost of technology substitution using a static approach that does not consider the evolution of technology [17,18]. This study consists of computing the abatement cost over the whole period of wind energy grid parity. The results suggest that, given the learning rate, cost target, and deployment speed of wind energy, climate finance can be structured to help align up-front capital subsidy with declining cost trajectory. In the absence of consistency between climate finance and technology roadmap, project-based Clean Development Mechanism (CDM) has already put into question the additionality of climate finance due to multiple domestic policies of the wind power sector in China [19]. In the context of global climate regime, new market mechanisms shift towards a sectoral approach to support Nationally Appropriate Mitigation Actions (NAMA) in developing countries [20,21]. Most of these initiatives are still at a conceptual level. Nevertheless, our quantitative and evidence-based analysis shows what design features of climate finance can help maintain coherence between global and domestic efforts.

The reminder of this article is organized as follows. Section 2 details methods and models. Section 3 presents data issues. Section 4 presents and discusses the results. Section 5 concludes with policy implications.

2. Method and models

2.1. Technology trajectory

We assume that wind technology follows an exponential growth path such that:

$$N_t = N_0 \cdot e^{\delta \cdot t} \tag{1}$$

Noting that δ measures the growth rate of cumulative wind capacity, which equals to $e^{\delta - 1}$.

The main spirit of learning models is that cost reductions will be achieved as a result of learning-by-doing and learning-by-searching activities. Learning-by-doing leads to increased labor efficiency, work specialization and methods improvement. Learning-by-searching measures the impact of R&D based knowledge stock on technology cost through design improvement, manufacturing optimization, economies of scale, and new materials or production process. The existing literature mostly uses public and private R&D expenditures to represent the state of knowledge stock. We use the simplest and most commonly used specification of one-factor learning-by-doing curve in following modeling exercise, while we empirically test the validity of two-factor learning curve combing learning-by-doing and learning-by-searching.[2] We return to a discussion of this issue below when reporting regression results. The one-factor learning curve can be expressed as:

$$C_t = C_o (N_t / N_0)^{-\alpha} \tag{2}$$

where[3]

- C_t andC_o are the capital cost level of wind technology at time t and at a starting point ($t = 0$), respectively;
- α is the learning-by-doing coefficient.

Based on Eq. (2), the learning-by-doing rate (LR) is subsequently defined as:

$$\mathrm{LR} = 1 - 2^{-\alpha} \tag{3}$$

Precisely, LR measures the relative cost reduction in percentage after each doubling of cumulative production.

At the breakeven time ($t = b$), cumulative installed capacity and capital cost of wind technology are denoted as N_b and C_b, respectively. Then, from Eq. (1), the breakeven time (T) can be expressed as follows:

$$T = \ln(N_b / N_0) \cdot (1/\delta) \tag{4}$$

With Eq. (2), Eq. (3) is equivalent to:

$$T = (-\delta \cdot \alpha)^{-1} \cdot \ln(C_b / C_0) \tag{5}$$

Clearly, the breakeven time depends on normalized breakeven cost (C_b/C_0), learning coefficient (α) and growth rate of cumulative capacity (δ).

2.2. Learning investment

We model a subsidy system based on investment subsidies. For defining an optimal subsidy, policy makers need to forecast the additional investment required to make a technology commercially viable, such that governmental intervention is no longer needed. In this paper, we use the well-known learning curve model to quantitatively assess this financing need. Following [16], we define learning investment as additional finance necessary to help achieve the cost competitiveness of wind technology as compared to a business-as-usual energy technology (see Fig. 3 in [16] for a graphical illustration).

We measure energy technology costs by unit of installed capacity. Thus, the total learning investment over the breakeven time (I_b), in the form of capital subsidy, can be integrated as

$$I_b = \int_{N_0}^{N_b} (C_b - C_0) d_N \tag{6}$$

[2] The two-factor learning curve is $C_t = C_0 (N_t/N_0)^{-\alpha} (KS_t/KS_0)^{-\beta}$ where KS_t and KS_0 are the knowledge stock at time t and at a starting point ($t = 0$), respectively; β is the learning-by-searching coefficient.

[3] Eq. (2) is equivalent to $N_b = (N_0) \cdot (C_b/C_0)^{-1/\alpha}$ at the breakeven time ($t = b$).